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Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm

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ABSTRACT

It is hard to predict wind power with high-precision due to its non-stationary and stochastic nature. The wind power has developed rapidly around the world as a promising renewable energy industry. The uncertainty of wind power brings difficult challenges to the operation of the power system with the integration of wind farms into power grid. Accurate wind power prediction is increasingly important for the stable operation of wind farms and the power grid. This study is combined support vector machine and improved dragonfly algorithm to forecast short-term wind power for a hybrid prediction model. The adaptive learning factor and differential evolution strategy are introduced to improve the performance of traditional dragonfly algorithm. The improved dragonfly algorithm is used to choose the optimal parameters of support vector machine. The effectiveness of the proposed model has been confirmed on the real datasets derived from La Haute Borne wind farm in France. The proposed model has shown better prediction performance compared with the other models such as back propagation neural network and Gaussian process regression. The proposed model is suitable for short-term wind power prediction.

1. Introduction

Energy shortage has become a serious issue, due to the expansion of production scale and consumer demand (Bagal et al., 2018). The wind power is regarded as one of the most promising industry to solve the energy crisis and has attracted due to its abundant source, little pollution and low cost (Jiao et al., 2018). In recent decades, the wind power industry developed rapidly all over the world, and the cumulative installed capacity of global wind power has continuously increased (Chitsaz et al., 2015). However, the fluctuation and intermittence of wind will cause non-stationary and stochastic nature of wind power, which has an adverse impact on the power system (Zhang et al., 2017). Especially, large-scale integration of wind power inevitably brings detrimental effects on the dispatching arrangement of the power grid and then reduces the reliability of the power grid (Shen et al., 2018). The wind power prediction is regarded an effective approach to solve such problem. For the electric power sector and wind farms, accurate wind power forecasting results are required to make appropriate generation, distribution and maintenance strategies. Therefore, accurate wind power prediction is essential for the integration of wind power and stable operation of the power system.

Based on the time range, the forecasting can be divided into four categories: long-term and medium-term forecasting (several weeks or months), short-term forecasting (several hours or several days), and ultra-short term forecasting (several minutes or several hours) (Yuan et al., 2015). The medium-term and long-term wind power forecasting can provide guidance for the maintenance plan and operation management of wind farms, while the short-term forecasting is used for economic dispatch of power system, energy reserve planning and electricity market operations (Kim and Hur, 2018). The ultra-short term forecasting is used for balancing load and the optimal optimization of spinning reserve, which has high requirements for prediction accuracy (Liu et al., 2018a). Short-term forecasting plays an important role in the coordination of

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wind turbines and economic dispatch planning, and has become the focus of current study.

Generally, the wind power prediction methods can be classified into deterministic prediction and probabilistic prediction. At present, most methods belong to the deterministic prediction, which can provide the predicted values on specific time. Common evaluation indexes include mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE) and so on. For deterministic prediction, the classical prediction models including support vector machines (SVM) and artificial neural network (ANN) have been widely used (Catalao et al., 2009). On the other hand, the probabilistic prediction can provide the probability distribution of wind power corresponding to the predicted time. The expected value of the probability distribution or the power value with the highest probability of occurrence is regarded as the predicted result of the wind power. Bayesian method and quantile regression are both commonly used probabilistic prediction methods (Bracale and Falco, 2015; Haque et al., 2014). In addition, the ensemble methods have also been used to make up for the limitations of a single classifier (Ren et al., 2015). The ensemble method, improving the versatility and robustness of a single estimator by combining several base estimators, can be divided into two categories: averaging method and boosting method. The main difference between the two categories is the combination method of base estimators. In the averaging method, each method is in a side-by-side relationship, and the hybrid model takes into account the impacts of each sub-method (Abedinia et al., 2019). The boosting method can enhance the ability of the basic model by combining different optimization methods.

To sum up, the SVM model is ideal for the prediction of short-term wind power due to its excellent learning ability in processing small sample data. Therefore, the SVM is chosen as the basic model for wind power prediction in this study. The parameters selection has a great impact on prediction performance of SVM. Traditional methods, such as grid search method, usually compare different parameter combinations to select the best performance. However, this type of method belongs to the enumeration method, which is incapable for large-scale calculation with high precision. To deal with this, an improved dragonfly algorithm (IDA) is proposed to optimize the parameters of SVM model. Based on the original dragonfly algorithm (DA), an adaptive learning factor and differential evolution strategy are introduced to improve the search ability. Thus, a hybrid model (IDA-SVM) combining IDA and SVM is established to predict short-term wind power. The model indicated from the experimental results that the performance of proposed model is superior to other models, including SVM optimized by DA (DA-SVM), SVM optimized by genetic algorithm (GA-SVM), SVM optimized by grid search method (Grid-SVM), back propagation neural network (BPNN) and Gaussian process regression (GPR). Therefore, the IDA-SVM model is believed to contribute to the accurate prediction of short-term wind power.

The remainder of this study is structured as follows: Section 2 presents the related theoretical approach and literature review. Section 3 introduces the classic SVM theory. In Section 4, a detailed introduction to DA and IDA is given. Section 5 describes the IDA-SVM prediction model, and the predicted results are discussed. In Section 6, the work, conclusions, and future work are summarized.

2. Literature review

Many efforts have been devoted to the wind power forecasting (Abdoos, 2016). In general, the wind power forecasting methods are summarized into three categories: physical methods, statistical methods and hybrid methods based on computational intelligence (Liu et al., 2018b). The numerical weather prediction is commonly employed to predict future weather phenomena and atmospheric conditions. The difference between physical and statistical methods is whether the numerical weather prediction is applied. Specifically, physical methods rely on the data from numerical weather prediction for further prediction. The power output of wind farm is calculated by the physical information of the mathematical model of wind turbine, after obtaining the information of wind farm location (Chang et al., 2017). Different with the physical methods, the statistical methods refer to predicting by the mapping relationship between the historical meteorological data and historical power data (Zhao et al., 2018). As a traditional statistical method, time series model has been widely applied in the economic, meteorological and other fields (Sun et al., 2018). The typical time series models include auto regressive (AR) models, auto regressive moving average (ARMA) models and etc (Karakus et al., 2017; Eissa et al., 2018). The time series method is more effective for ultra-short term prediction since the wind power has strong autocorrelation in a short time. However, the time series model lacks nonlinear fitting ability, which limits its prediction ability. In addition, the conventional statistical methods also include the quantile regression and stochastic differential equation (Wan et al., 2017; Iversen et al., 2017). These two methods are suitable for probabilistic prediction of wind power and can provide uncertain information in power prediction.

In addition to conventional statistical methods, the machine learning models, such as artificial neural networks and Gaussian process regression, support vector machine, extreme learning machine (ELM) and Bayesian methods, are extensively applied in wind power forecasting (Zjavka and Misak., 2018). Furthermore, the combination of intelligent algorithms and statistical approaches has further developed the prediction technology. Fang and Chiang (2017) put forward a model involving the Gaussian process and new composite covariance function. By verifying the competition data, the performance of hybrid model is proved to be superior to other competitors. A novel perdition system with deep neural network was adopted by Qureshi et al. (2017). The effectiveness of the system was verified by three error indexes of statistical analysis. Ghadimi et al. (2018) proposed a forecast engine based on the radial neural network (RNN) and Elman neural network (ENN). In addition, a chaotic binary shark smell optimization algorithm was employed to optimize the parameters of the engine. In the research from Osorio et al. (2015), a novel hybrid method consists of four different algorithms was investigated to promote the operation speed and predictive accuracy of the system. It was proved that the methodology is accurate and effective in the Portuguese system. Moreover, Yuan et al. (2017) put forward the time series approach to handle the wind power data and extract the linear component. Then the linear component and nonlinear components were imported into the least squares support vector machine. By combining the ARMA and boosting algorithm, Jiang et al. (2017) employed a hybrid model to process the uncertainty of wind. Considering the mean absolute error, normalized mean absolute error and root mean squared error, the performance of proposed hybrid method has outperformed other traditional methods. Based on neural network and improved shark smell algorithm, Mirzapour et al. (2019) presented an accurate forecast method, which has been used to forecast short-term wind and solar power effectively. Shao et al. (2018) explored the infinite feature selection method to perform mapping operations on the classified data sets and employed the recurrent neural network as wind forecasting system after classifying the features of time series. And the prediction accuracy of proposed method is higher than those traditional approaches with the standard dataset.

As a promising model in statistical learning theory, SVM has advantages in high-dimensional and nonlinear modeling. Based on the structural risk minimization principle, the complex problems are transformed into convex quadratic programming problem. Therefore, it can overcome the over or under learning problems inherent in methods, such as neural networks. On the other hand, it also has strong nonlinear classification ability. The SVM has been applied in many fields, such as feature recognition, regression analysis and prediction (Liu et al., 2018c). Based on SVM technology, Soualhi et al. (2015) conducted the research about the degree of ball bearing degradation to improve the reliability and safety of the industrial motor. Chen et al. (2015) used support vector regression model to predict daily tourist flow on holiday. The feasibility of model is proved by the daily flow data of historical visitors in Mount Huang. In order to improve the safety of investment forecast for the power grid, Dai et al. (2018) adopted differential evolution (DE) and grey wolf optimization to improve the prediction ability of SVM. The model accurately predicted grid investment of China in the next four years and provided guidance for investment plans of the power grid. Cao and Wu (2016) employed SVM to forecast the monthly power consumption and the predicted results proved the feasibility of the SVM for electricity consumption forecasting. Yang et al. (2018) proposed a typhoon rainfall prediction model based on SVM and the experimental results illustrates its good performance in rainfall prediction, especially for long lead time prediction. In view of the advantages of SVM in dealing with small samples and nonlinear data, the SVM is chosen as the basic model for wind power prediction in this study.

The performance of SVM model highly depends on internal parameters, so it is important to adopt effective algorithm to choose the optimal parameters (Amroune et al., 2018). As a novel swarm intelligent algorithm, dragonfly algorithm has attracted the attention of scholars since proposed. Many improved methods have been proposed to improve the ability of DA. Hariharan et al. (2018) put forward a binary dragonfly optimization algorithm, which adopts a new updating mechanism and elite strategy. In terms of the concept of historical optimal position of individual and population, Ranjini and Murugan, 2017 proposed a memory based hybrid dragonfly algorithm. The differential evolution (DE) is an adaptive global search algorithm, which has shown excellent performance in the Congress on Evolutionary Computation (Storn and Price. 1997). The differential evolution strategy plays an important role in improving the global search ability and has been introduced by many algorithms to improve performance. Zuo and Xiao (2014) used an operator that hybrids DE and particle swarm optimization (PSO) to solve the dynamic optimization problem. Wu et al. (2019) proposed a new method based on the improved grey wolf optimization to find the optimal parameters of ELM. The application of differential evolution strategy enhances the performance of origin algorithm. Elaziz et al. (2019) introduced an intelligent method that combines moth search algorithm and differential evolution algorithm to solve cloud task scheduling. Therefore, this study proposes an improved dragonfly algorithm (IDA) involving differential evolution strategy and adaptive learning factor, which is used to choose the parameters of SVM. Thus, an IDA-SVM prediction model is established to predict the short-term wind power.

3. Support vector machine

The support vector machine adopts the structural risk minimization principle and has excellent generalization ability (Cortes and Vapnik, 1995). Considering the capability of adaptive learning and nonlinear approximation, the SVM has distinct advantages in handling small samples and nonlinear data (Wang and Hu, 2015). For a given dataset, the i-th input sample x_i in a low-dimensional space is mapped to a higher-dimensional vector space by a nonlinear mapping function $\phi(x)$. The linear regression function established in high dimensional space is simplified as:

$$f(x) = w \cdot \phi(x) + bx \in R^d, b \in R \tag{1}$$

where ω represents the weight, b is the parameter of bias, $f(x)$ denotes the predicted values, x indicates the input vector in the sample space, R stands for the real number field and d is the dimension of sample space.

The support vector regression problem is replaced with a mathematical optimization problem with constraints by applying the structural risk minimization principle. The fitting error is taken into account and two slack variables ξ_i and ξ_i^* are added. The optimization function and constraints are as follows (Chang and Lin, 2011):

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{2}$$

$$\begin{cases} y_i - \omega \cdot x_i - b \le \varepsilon + \xi_i \\ \omega \cdot x_i + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i \ge 0 \\ \xi_i^* \ge 0 \qquad i = 1, 2 \ldots n \end{cases} \tag{3}$$

where $i = 1, 2, \ldots, n$, n is the number of samples. C is the penalty factor, ε is the loss function, $y_i = f(x_i)$.

The solution of the equation can be transformed into solving the saddle point of the Lagrange equation by introducing the Lagrange multiplier. After calculating the partial derivative of the equation and applying the duality theorem, the final optimization problem is presented as:

$$\begin{aligned} &\max\left\{ -\frac{1}{2}\sum_{i,j=1}^{n}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)K\left(x_i, x_j\right) + \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right)y_i - \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*)\right\} \\ &\text{s.t.} \quad \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) = 0 \qquad \alpha_i, \alpha_i^* \in [0, C] \end{aligned} \tag{4}$$

where α_i, α_i^* are the Lagrange multiplier and $\alpha_i > 0$, $\alpha_i^* > 0$, $K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$ represents kernel function, $i, j = 1, 2, \ldots, n$

Furthermore, the nonlinear function is expressed as:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b \tag{5}$$

The radial basis function is regard as an ideal classification function due to its wider convergence regions and higher resolution. In this study, the radial basis function is chosen as the kernel function, which is defined as:

$$K(x_i, x_j) = \exp\left(-\frac{\|x - x_i\|^2}{2\delta^2}\right) \tag{6}$$

where, δ is the width of the radial basis kernel function.

The application of radial basis function is helpful to show the relationship between the original input and output space. In the traditional SVM, the penalty factor C and the parameter δ are chosen empirically. In view of the diversity and complexity of the input data, this approach will increase the randomness of the prediction and lead to unreliable results. In order to solve such problem, the improved dragonfly algorithm is used to choose optimal parameters of SVM.

4. Dragonfly algorithm and improved dragonfly algorithm

The structure of the original dragonfly algorithm and improved dragonfly algorithm are introduced detailed in this section. In addition, the flow of improved algorithm is provided.

4.1. Dragonfly algorithm

The dragonfly algorithm is a novel metaheuristic algorithm based on the behavior of dragonflies (Mirjalili, 2016). There are five behaviors in the dragonfly population, namely separation, alignment, cohesion, the behavior of foraging and eluding enemies.

These behaviors are represented by the following mathematical models using Eqs. (7)-(11).

(1) The behaviors of avoiding collisions:

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{7}$$

where $j = 1, 2, \ldots, N$, $i = 1, 2, \ldots, N_p$, N is the number of neighbouring individuals, and N_p is the number of population. X denotes the position of the current individual, X_j is the position of the j-th neighbouring individual.

(2) The behavior of maintaining the coordinated flight with the dragonfly group:

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{8}$$

where V_j represents the velocity of the j-th neighbouring individual.

(3) The behavior of moving closer to each other for every individual:

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{9}$$

(4) The behavior of foraging:

$$F_i = X^+ - X \tag{10}$$

where X^+ represents the position of the current individual with optimal fitness value.

(5) The behavior of eluding enemies:

$$E_i = X + X^- \tag{11}$$

where X^- represents the position of the current individual with worst fitness value.

In order to update the location of dragonflies and simulate flight behavior in the search space, two vectors: step size (ΔX) and position (X) are introduced. The step vector is computed as follows:

$$\Delta X^{t+1} = w\Delta X^t + (sS_i + aA_i + cC_i + fF_i + eE_i) \tag{12}$$

where s, a, c, f, e indicate the weights of five behaviors, ω is the inertia weight, t is the current iteration.

The position vector is updated as follows:

$$X^{t+1} = X^t + \Delta X^{t+1} \tag{13}$$

When there are no adjacent individuals, a random walk strategy is introduced to enhance the randomness of the search. In this case, the equation of position vector is shown in Eq. (14):

$$X^{t+1} = Levy(d) \times X^t + X^t \tag{14}$$

where d represents the dimension of the dragonfly individual.

The Levy flight strategy is described as in Eqs. (15)-(16):

$$Levy(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{15}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{1/\beta} \tag{16}$$

where r_1, r_2 are two stochastic numbers in [0,1], β is a constant, which is taken as 1.5, $\Gamma(x) = (x-1)!$.

4.2. Improved dragonfly algorithm

This sub-section discusses the (1) adaptive learning factor; (2) differential evolution strategy; and (3) flow of improved algorithm.

4.2.1. Adaptive learning factor

The positions of dragonflies in the search space are randomly distributed. When there are no nearby particles around the current particle, the particle performs random walk strategy. This situation will slow down the convergence trend and reduce the convergence accuracy under the limited number of iterations. An adaptive learning factor is introduced to solve this issue. And the relative change rate of the fitness value of the dragonfly is defined:

$$\nu = \frac{|f(X_i^t) - f(X_{best}^t)|}{f(X_{best}^t) + \eta} \tag{17}$$

where $i = 1, 2, \ldots, N_p$, X_i^t represents the i-th individual of the dragonfly at the t-th iteration. $f(X_i^t)$ is the fitness value of the i-th individual at the t-th iteration, $f(X_{best}^t)$ is the optimal fitness value of dragonfly in the t-th iteration, η is the smallest constant in the computer to avoid zero-division-error.

The adaptive learning factor of the i-th dragonfly in the t-th iteration is expressed as follows:

$$c_i^t = \frac{1}{1 + e^{-v}} \tag{18}$$

When there are adjacent individuals around, the position vector of the i-th dragonfly at the t-th iteration is described as follows:

$$X_i^{t+1} = c_i^t X_i^t + \Delta X_i^{t+1} \tag{19}$$

Otherwise, the equation of position vector is calculated as follows:

$$X_i^{t+1} = c_i^t X_i^t + Levy(d) \times X_i^t \tag{20}$$

4.2.2. Differential evolution strategy

When the algorithm falls into the local optimal solution, the search process will be stagnated. In order to avoid premature convergence, the differential evolution strategy is introduced to maintain the diversity of population. In addition, the DE/best/1 mutation strategy and dynamic scaling factor are adopted. The specific equation is as follows (Xiang et al., 2015):

$$H_i^t = X_{best}^t + F_i^t \bullet \left(X_{p1}^t - X_{p2}^t\right) \tag{21}$$

where H_i^t is the mutant vector, $i = 1, 2, \ldots, N_p$. $p_1, p_2 \in \{1, 2, \ldots, N_p\}$ *are random integers and* $p_1 \neq p_2$. F_i^t is the scaling factor and can be calculated below:

$$F_i^t = F_{inital} + \left(F_{final} - F_{inital}\right) \bullet \frac{f(X_i^t) - f(X_{best}^t)}{f(X_{worst}^t) - f(X_{best}^t)} \tag{22}$$

where F_{inital} *and* F_{final} are two constants $f(X_{worst}^t)$ is the worst fitness value among the population in the t-th iteration.

After obtaining the mutant vector, the crossover operation is performed to produce a trial vector $V_{ij}^t = (V_{i1}^t, V_{i2}^t, \cdots, V_{id}^t)$ using Eq. (23):

$$V_{ij}^t = \begin{cases} H_{ij}^t & \text{if } j = j0 \text{ and } \text{rand}(0,1) \leq pCR \\ X_{ij}^t & \text{else} \end{cases} \tag{23}$$

where $j = 1, 2, \ldots, d, j0 \in \{1, 2, \ldots, \mathrm{d}\}$ is a random dimension, pCR represents cross probability within the range of [0,1].

Finally, the population is updated by comparing the fitness value. The selection strategy is shown as follows:

$$X_i^{t+1} = \begin{cases} V_i^t & \text{if } f(V_i^t) < f(X_i^t) \\ X_i^t & \text{else} \end{cases} \tag{24}$$

4.2.3. The flow of improved dragonfly algorithm

The specific steps of IDA are depicted as follows:

(1) Parameters setting. Set the maximum number of iteration, particle dimension, population size, upper and lower boundaries of particles.
(2) Initialize the position vector and step vector.
(3) Start iteration. Update the weight coefficient and evaluate the fitness values of population. Then update the position of the food and enemy.
(4) Update the value of S, A, C, F, E using Eqs. (7)-(11) and update the step vector using Eq. (12). When there is no neighbouring solution around the current individual, update the position using Eq. (20). Otherwise, update the location using Eq. (19).
(5) Perform the differential evolution strategy on each individual using Eqs. (21)-(24).
(6) Judge whether the termination condition is satisfied. If so, stop the iteration and export the final result. Otherwise, return step 3.

The flow chart of IDA is shown in Fig. 1.

A set of classical functions are selected for testing the optimization ability of IDA. The first group contains two unimodal functions and the second group contains three multimodal functions. Specific description of dimension, the optimal value and domain is shown in Table 1.

To validate the performance of IDA, the DA, whale optimization algorithm (WOA), ant lion optimization (ALO) algorithm and PSO were introduced for comparison. The entire experiment was performed on Microsoft Windows 7 operating system and MATLAB R2017a software. The computer configuration is specifically described as: Core i5, 3.2 GHz, 8 GB RAM. Five functions ran 30 times independently, and the average value and standard deviation are chosen as the evaluation indexes. The detailed parameters are shown in Table 2. The ub and lb are the upper and lower boundaries of search. The parameters of ALO and WOA are taken from the default values (Mirjalili, 2015; Mirjalili and Lewis, 2016). The statistical results are presented in Table 3.

Table 3 indicates that the IDA outperforms other algorithms from the perspective of convergence accuracy. In addition, the standard deviation of the solution calculated by IDA is much smaller than other algorithms, which proves strong stability of proposed algorithm. From the results, the convergence accuracy and stability of IDA are better than the other four algorithms significantly.

5. Experimental results and discussion

This section presents the IDA-SVM prediction model and simulation. It contains: (1) the source and type of the data set; (2) the method of data processing; (3) objective function and evaluation indexes; (4) flow chart of the IDA-SVM prediction model; and (5) experimental results and discussions.

5.1. Data collection

The La Haute Borne wind farm is an open data windfarm, located in Grand Est of northeastern France. In this study, the dataset of La Haute Borne wind farm is collected and used (Engie, 2018). There are four wind turbines in wind farm and the information is provided as follows: Rated power: 2050 KW, Hub height: 80 m, Altitude: 411 m, Rotor diameter: 82 m. This study selects the operating data of the first wind turbines with a total of 8778 data points in 2017 and the sampling time period is 1 h. The operation data in the winter and autumn are selected as the validation data to evaluate the proposed method comprehensively. In addition to wind power, the data set includes other variables, such as wind speed, wind direction and temperature. Since the wind is considered as the main factor that affects wind power, the historical data of wind speed and wind direction are chosen as input variables. 144 samples in 6 consecutive days are selected as training samples to predict wind power in the next 48 h. And the ratio of training samples to test samples is 3:1.

5.2. Data processing

(1) Normalization of the wind speed and wind power

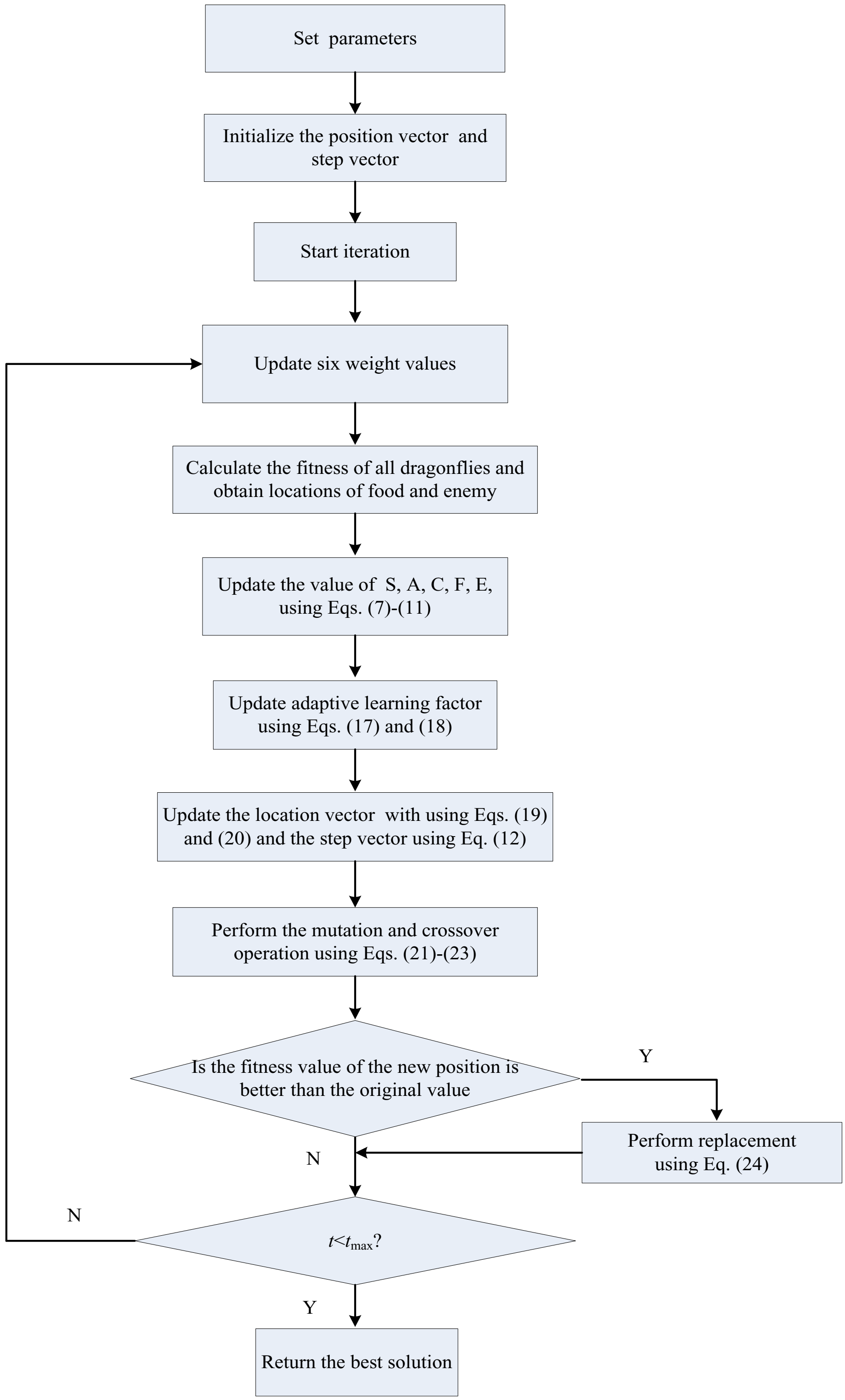

Fig. 1. The flow chart of IDA.

The large fluctuation of sample data will affect the prediction accuracy and lead to uncertainty of solution. The normalization of data can reduce the impact of sample fluctuations and enhance the prediction performance. In this process, the linear transformation equation is used to normalize wind speed. The normalized equation is shown as follow:

$$V_{nor,\ i} = \frac{V_i - V_{\min}}{V_{\max} - V_{\min}} \tag{25}$$

where $V_{nor,i}$ is the wind speed value after normalization, V_i is the actual wind speed, $V_{\min}$ and $V_{\max}$ are the minimum and maximum values in actual wind speed.

Table 1
The description of test function.

Function	Dim	Range	$f_{\min}$
Unimodal function			
$f_1(x) = \sum_{i=1}^{n} x_i^2$	10	[-100,100]	0
$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	10	[-10,10]	0
Multimodal function			
$f_3(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	10	[-5.12,5.12]	0
$f_4(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} - \exp\left[\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right]\right) + 20 + e$	10	[-32,32]	0
$f_5(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	10	[-600,600]	0

Table 2
Parameter settings of different algorithms.

Algorithm	number of max iterations	size of population		
	500	40		
IDA	levy flight constant 1.5	inertial weights [0.9,0.4]	*pCR* 0.6	*scaling factor,* [0.1,0.9]
DA	levy flight constant 1.5	inertial weights [0.9,0.4]		
PSO	C_1 1.49445	C_2 1.49445	$v_{\max}$ 0.4*(ub-lb)	

Table 3
The statistical results of IDA and other algorithms.

Functions	Statistical indicator	IDA	DA	ALO	PSO	WOA
$f_1(x)$	Average	9.10e-106	4.80	4.36e-09	2.56	3.57e-76
	Std	4.81e-105	10.61	1.90e-09	1.37	1.95e-75
$f_2(x)$	Average	3.18e-53	1.51	0.48	0.44	1.70e-52
	Std	1.40e-60	1.24	1.02	0.13	8.06e-52
$f_3(x)$	Average	0	28.35	19.73	8.50	0
	Std	0	12.77	7.76	2.29	0
$f_4(x)$	Average	4.32e-15	2.30	0.20	2.05	4.44e-15
	Std	6.48e-16	1.11	0.48	0.60	2.64e-15
$f_5(x)$	Average	0.012	0.44	0.19	0.88	0.021
	Std	0.031	0.26	0.10	0.12	0.05

The normalization process of wind power also adopts the linear transformation, which is same as the wind speed. Thus, the operation is not repeated.

(2) Normalization of the wind direction

The value of the wind direction ranges from between 0 and 360. When normalizing wind direction data, the wind direction angle is firstly converted into the radians. Then the corresponding sine and cosine values are taken as input data. Therefore, the normalization results include two sets of data: the sine and cosine values of wind direction data.

5.3. Objective function and evaluation indexes

The mean squared error (MSE) has a widely application in the statistic field, which can reflect the prediction accuracy effectively. Therefore, the MSE is chosen as the objective function for evaluating the performance of the proposed model. The smaller fitness value represents better prediction accuracy. The objective function is described as follow:

$$Fitness = \frac{1}{n}\sum_{i=1}^{n}(P_i - Y_i)^2 \tag{26}$$

where P_i is the actual value of the wind power, and Y_i is the predicted value, n is the number of training samples.

It is difficult to make a comprehensive evaluation using the single error index. The RMSE is usually used to express the degree of dispersion of the results. The MAE and MAPE can indicate the deviation of the prediction. In addition, the coefficient of determination (R^2) is adopted to measure the linear correlation between the actual value and predicted value. In view of the large amplitude of the original data, the normalized evaluation indexes are uniformly adopted. These indexes are shown below (Gao et al., 2019; Mladenovic et al., 2016).

$$E_{NRMSE} = \frac{1}{P}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - Y_i)^2} \times 100\% \tag{27}$$

$$E_{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_i - Y_i}{P_i}\right| \times 100\% \tag{28}$$

$$E_{NMAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_i - Y_i}{P}\right| \times 100\% \tag{29}$$

$$R^2 = \frac{\left(\sum_{i=1}^{N}\left(P_i - \overline{P}_i\right)\cdot\left(Y_i - \overline{Y}_i\right)\right)^2}{\sum_{i=1}^{N}\left(P_i - \overline{P}_i\right)\cdot\sum_{i=1}^{N}\left(Y_i - \overline{Y}_i\right)} \tag{30}$$

where P_i represents the i-th actual wind power value, Y_i represents i-th predicted value of wind power, N is the total number of test samples, P represents the rated power of wind turbine, $\overline{P}_i$ and $\overline{Y}_i$ are average value corresponding to the true and predicted values.

5.4. The IDA-SVM forecasting model

The prediction process of the IDA-SVM prediction model is

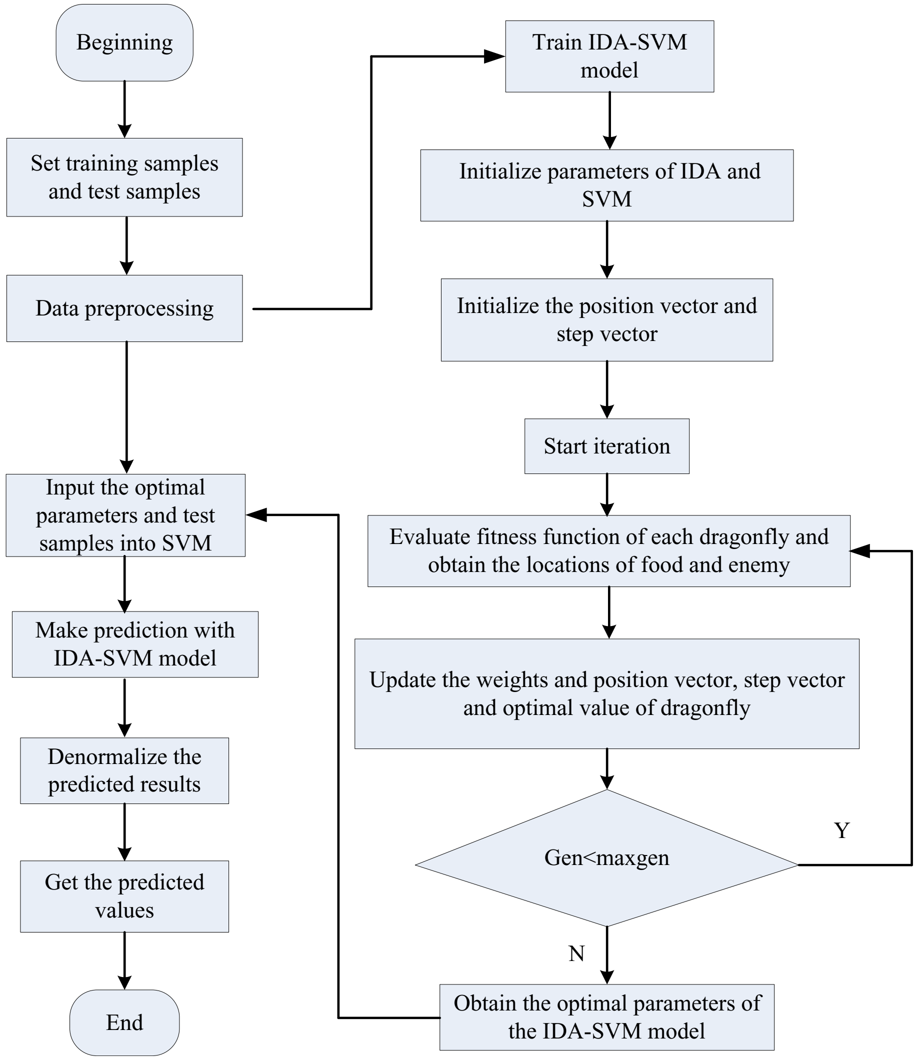

Fig. 2. Flow chart of the IDA-SVM model for wind power prediction.

depicted as follows:

- Step 1: Set the input and output variables. In Section 5.1, the training set and test set are determined.
- Step 2: Data processing. The wind power, wind speed and wind direction are normalized to achieve accurate prediction. The specific process is shown in Section 5.2.
- Step 3: Initialize the parameters of IDA and SVM.
- Step 4: Initialize the position vector and step vector.
- Step 5: Start iteration. Calculate the fitness value of each particle by the fitness function and update the weight coefficient, particle positions, and step vector.
- Step 6: Judge whether the termination condition is reached. If so, stop the iteration and record the optimal parameter. Otherwise, return step 5.

Table 4
Parameter settings of different models.

Parameters	The maximum number of iterations	Number of population	Dimension	Penalty parameter	Kernel parameter
	100	20	2	[0.1, 1200]	[0.01, 100]
IDA-SVM	levy flight constant	inertial weights	*pCR*	*scaling factor*	
	1.5	[0.9, 0.4]	0.6	[0.2,0.8]	
DA-SVM	levy flight constant	inertial weights			
	1.5	[0.9, 0.4]			
GA-SVM	crossover probability	mutation probability	gap		
	0.6	0.01	0.9		
Grid-SVM	*C*_step	δ_step			
	10	1			
BPNN	Maximum number of training steps	Learning rate	Convergence error	Number of hidden layers	
	100	0.1	0.00004	8	

Table 5
The evaluation indexes of predicted results in winter dataset.

Models	E_{NRMSE}	E_{NMAE}	E_{MAPE}	R^2
IDA-SVM	3.25%	2.75%	10.58%	0.9791
DA-SVM	4.42%	3.68%	13.06%	0.9607
GA-SVM	4.20%	3.48%	12.54%	0.9610
Grid-SVM	3.80%	3.09%	10.84%	0.9770
BPNN	8.70%	5.52%	13.46%	0.8994
GPR	10.89%	8.23%	19.92%	0.9765

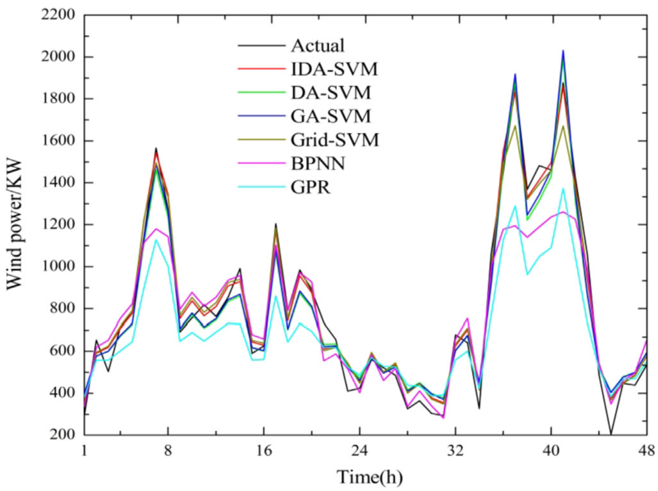

Fig. 3. Wind power forecasting results of six models in winter dataset.

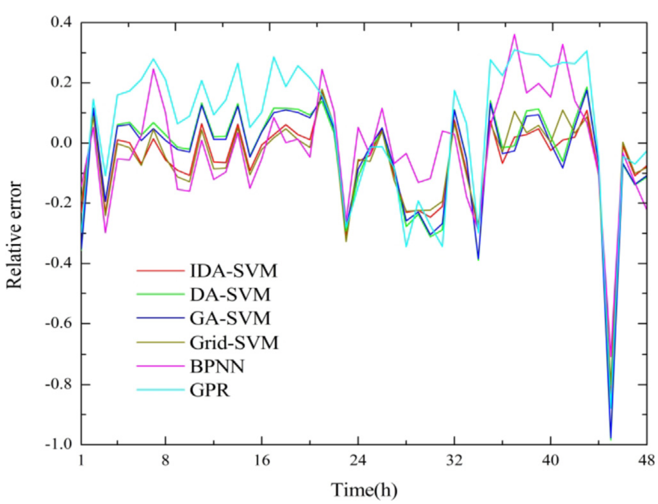

Fig. 4. The relative error curves of six models in winter dataset.

- Step 7: Input the optimal parameters into the SVM model and predict the test samples.
- Step 8: Perform anti-normalization operation on the predicted result and save the final results.

Fig. 2 presents the flow chart of the IDA-SVM model for wind power prediction.

5.5. Experimental results and discussions

In order to verify the performance of IDA-SVM model, the DA-SVM model, GA-SVM model, Grid-SVM model, BPNN and GPR are used to predict the wind power of the same sample points. The true wind power is compared with the predicted results of the six models respectively. The detailed parameters of each model are shown in Table 4. Table 5 provides the comparison results of different models in January.

Table 5 shows the proposed model is more accurate than other models and the three error indicators of the IDA-SVM are the smallest among all the methods. The prediction error is reduced by 26.4%, 25.27% and 23.44% compared to the DA-SVM model, which demonstrates the effectiveness of improvement strategy. Thus, IDA has shown the higher prediction precision compared with the traditional grid search method and other algorithms. In addition, the prediction performance of the SVM-based models is better than BPNN and GPR, which shows the advantage of SVM in small sample prediction. It can be found that the IDA-SVM model has the highest performance among six prediction models. Fig. 3 presents the predicted results of six models in January and the relative error curves of 48 predicted points are shown in Fig. 4.

Fig. 3 indicates the wind power varies greatly within 48 h and shows higher volatility. The power curve predicted by IDA-SVM is closer to the actual value. Fig. 4 shows the relative error of the IDA-SVM is the smallest among all the models. Compared with BPNN and GPR, the SVM-based model has more accurate predicted value. In addition, the relative absolute error of predicted value is counted. The statistical results under different relative absolute error are presented in Table 6. The sample points with relative absolute error that is lower than 3%, 5%, 15%, 25% are recorded. From the statistical results, the proposed model shows better prediction accuracy. Approximately the absolute error of 93.75% sample points are less than 25%, while the absolute error of 27% sample points are less than 3%. So, the proposed model has shown excellent prediction ability compared with other methods. In addition to winter data set, the wind power data from September in autumn is also adopted for validation to eliminate the prediction contingency. The predicted results of different models in September are listed in Table 7.

Table 7 presents three error indexes of the proposed model are better than other models. The three error indicators of the IDA-SVM model are 5.24%, 4.04% and 8.64%, which shows excellent prediction performance. Compared with other models such as BPNN and GPR, three error indicators of the IDA-SVM are significantly reduced. In addition, when compared with the other three

Table 6
Accuracy estimation of predicted point for winter dataset.

Model	<3%		<5%		<15%		<25%	
	number	percentage	number	percentage	number	percentage	number	percentage
IDA-SVM	13	0.27	16	33.33	38	79.17	45	93.75
DA-SVM	10	0.208	15	31.25	38	79.17	41	85.42
GA-SVM	9	0.1875	14	29.17	37	77.08	41	85.42
Grid-SVM	9	18.75	16	33.33	38	79.17	45	93.75
BPNN	5	10.42	11	22.97	32	66.67	42	87.5
GPR	3	6.25	4	8.33	18	37.5	29	60.42

Table 7
The evaluation indexes of predicted results in autumn dataset.

Models	E_{NRMSE}	E_{NMAE}	E_{MAPE}	R^2
IDA-SVM	5.24%	4.04%	8.64%	0.9544
DA-SVM	6.17%	5.15%	13.41%	0.9282
GA-SVM	6.52%	5.43%	14.31%	0.9200
Grid-SVM	5.87%	4.56%	10.27%	0.9311
BPNN	9.95%	7.90%	17.58%	0.8739
GPR	8.60%	6.37%	12.19%	0.8968

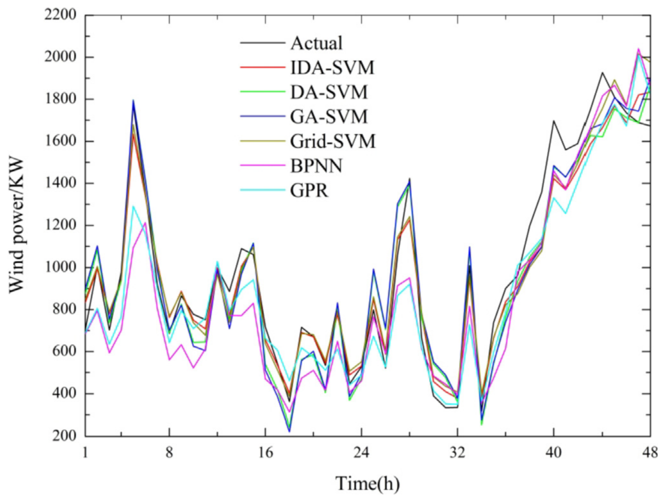

Fig. 5. Wind power forecasting results of six models in autumn dataset.

prediction models using SVM, the prediction accuracy mainly depends on the performance of the algorithm. From the predicted results, the IDA is superior to the other algorithm. Especially, the MAPE of proposed model is significantly reduced. In addition, the R^2 of the proposed model is 0.9544, which indicates that the predicted trend of the proposed model is more accurate than other models.

Fig. 5 depicts the prediction curves of different models in September dataset. The IDA-SVM prediction curve is closer to actual curve. Fig. 6 shows the relative error curves in autumn data set and the fluctuation trend of each curve is different, and the prediction error at different points also varies greatly. The relative error curve of the proposed model is more stable, as there is no point with large deviation compared with other models. Table 8 provides the distribution of relative absolute error of the predicted points. In Table 8, the absolute error of all sample points predicted by the IDA-SVM model are less than 25%, while the optimal accuracy of other models is only 89.58%. Besides, the proposed model has also achieved the high level of performances within the other error ranges. So, the prediction performance of the IDA-SVM model is superior to other models. The IDA-SVM model has shown higher prediction accuracy and stability in different season of the year.

6. Concluding remarks

Accurate wind power forecasting promotes the utilization of wind energy and stability of grid operation. It is difficult to achieve accurate prediction using single prediction method due to the intermittent and random nature of wind power. In this study, a short-term wind power prediction model namely IDA-SVM is proposed to improve the prediction accuracy of wind power. The simulation results show that the proposed model has higher prediction accuracy than other prediction models and is suitable for short-term wind power prediction. Specifically, the findings of this study are as follows:

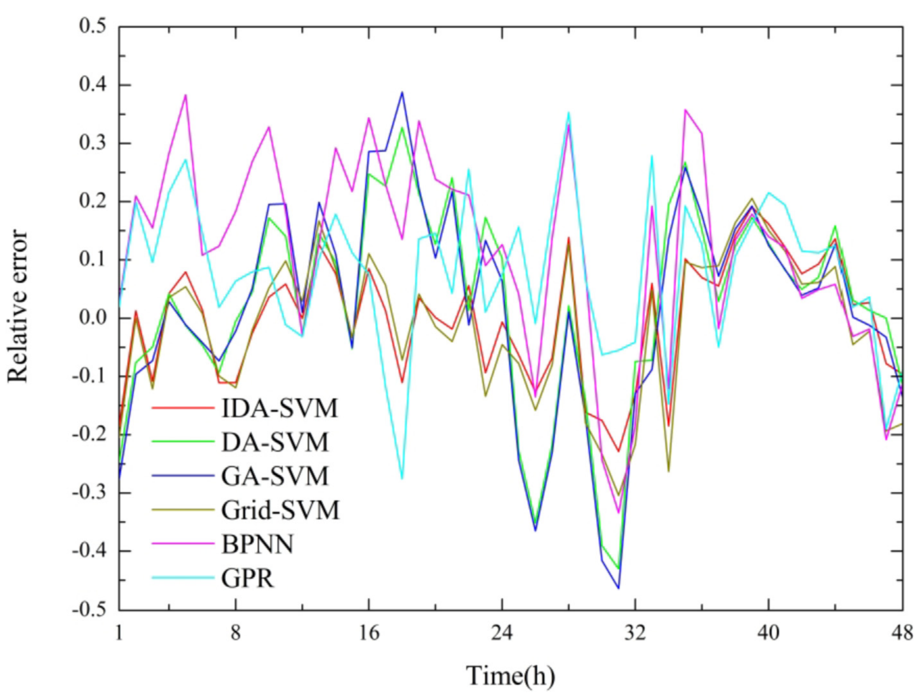

Fig. 6. The relative error curves of six models in autumn dataset.

Table 8
Accuracy estimation of predicted point for autumn dataset.

Model	<3%		<5%		<15%		<25%	
	number	percentage	number	percentage	number	percentage	number	percentage
IDA-SVM	10	20.82	14	29.17	41	85.42	48	100
DA-SVM	8	16.67	14	29.17	30	62.50	43	89.58
GA-SVM	8	16.67	11	22.92	29	60.42	40	83.33
Grid-SVM	6	12.50	14	29.17	35	72.92	46	85.83
BPNN	3	6.25	8	16.67	23	47.92	37	77.08
GPR	6	12.50	11	22.92	33	68.75	43	89.58

(1) Adaptive learning factor and differential evolution strategy are taken to boost optimization ability of DA. The performance of IDA has been validated by a set of unimodal and multimodal test functions.
(2) The proposed IDA is used to choose the optimal parameters considering the parameter influence on the performance of SVM. The hybrid IDA-SVM model is established to predict the short-term wind power.
(3) The winter and autumn data set from La Haute Borne wind farm is used as testing set to validate the prediction ability of proposed model. The proposed model can effectively improve the accuracy of wind power prediction compared with the DA-SVM, GA-SVM, Grid-SVM, BPNN and GPR models.
(4) Five evaluation indexes are used to evaluate the performance of model. The three prediction errors, trend and accuracy of the proposed model are superior to other models, especially for BPNN and GPR models.

The contributions of this study are presented as follows. (1) An IDA-SVM prediction model combining IDA and SVM is proposed, which extends the short-term wind power forecasting method; (2) The proposed model is compared to other machine learning models. The prediction difference between different models is provided by experimental results; (3) The performance of the proposed model is analyzed synthetically with the datasets in different seasons, and the prediction accuracy of the proposed model is proved to be superior to other models; and (4) The proposed method is beneficial to reduce the impact of the wind power grid-connection on power system and provide reference for the dispatching plan of the power system.

This study still need further research. Since the proposed model chooses SVM as the basic model, the prediction accuracy of proposed model depends on the regression ability of the SVM itself. When dealing with large sample, the accuracy of model may decrease. The future study should introduce more models such as Least squares support vector machine, grey model and other models, which can provide more choices in the prediction field. In addition, the hybrid model combing different methods should be investigated. Therefore, further study will concentrate on several directions: (1) Applying the proposed model to other fields, such as photovoltaic power generation forecast; and (2) Adopting more advanced methods to enhance the prediction accuracy.

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Nomenclature

ALO	Ant lion optimization
GPR	Gaussian process regression
ANN	Artificial neural network
IDA	Improved dragonfly algorithm
AR	Auto regressive
IDA-SVM	Support vector machine optimized by improved dragonfly algorithm
ARMA	Auto regressive moving average
MAE	Mean absolute error
BPNN	Back propagation neural network
MAPE	Mean absolute percentage error
DA	Dragonfly algorithm
MSE	Mean squared error
DA-SVM	Support vector machine optimized by dragonfly algorithm
NMAE	Normalized mean absolute error
DE	Differential evolution
NRMSE	Normalized root mean squared error
ELM	Extreme learning machine
PSO	Particle swarm optimization
ENN	Elman neural network
RMSE	Root mean squared error
GA	Genetic algorithm
RNN	Radial neural network
GA-SVM	Support vector machine optimized by genetic algorithm
SVM	Support vector machine
Grid-SVM	Support vector machine optimized by grid search method
WOA	Whale optimization algorithm

References

Abdoos, A.A., 2016. A new intelligent method based on combination of VMD and ELM for short term wind power forecasting. Neurocomputing 203, 111–120.
Abedinia, O., Zareinejad, M., Doranehgard, M.H., Fathi, G., Ghadimi, N., 2019. Optimal offering and bidding strategies of renewable energy based large consumer using a novel hybrid robust-stochastic approach. J. Clean. Prod. 215, 878–889.
Amroune, M., Bouktir, T., Musirin, I., 2018. Power system voltage stability assessment using a hybrid approach combining dragonfly optimization algorithm and support vector regression. Arabian J. Sci. Eng. 43 (6), 3023–3036.
Bagal, H.A., Soltanabad, Y.N., Dadjuo, M., Wakil, K., Ghadimi, N., 2018. Risk-assessment of photovoltaic-wind-battery-grid based large industrial consumer using information gap decision theory. Sol. Energy 169, 343–352.
Bracale, A., De Falco, P., 2015. An advanced bayesian method for short-term probabilistic forecasting of the generation of wind power. Energies 8 (9), 10293–10314.
Cao, G., Wu, L., 2016. Support vector regression with fruit fly optimization algorithm for seasonal electricity consumption forecasting. Energy 115, 734–745.
Catalao, J.P.S., Pousinho, H.M.I., Mendes, V.M.F., 2009. An approach for short-term wind power forecasting in Portugal. Eng. Intell. Syst. Electr. Eng. Commun. 17 (1), 5–11.
Chang, C.C., Lin, C.J., 2011. LIBSVM: a library for support vector machines. Acm Trans. Intell. Syst. Technol. 2 (3), 27.
Chang, G.W., Lu, H.J., Chang, Y.R., Lee, Y.D., 2017. An improved neural network-based approach for short-term wind speed and power forecast. Renew. Energy 105, 301–311.
Chen, R., Liang, C.-Y., Hong, W.-C., Gu, D.-X., 2015. Forecasting holiday daily tourist flow based on seasonal support vector regression with adaptive genetic algorithm. Appl. Soft Comput. 26, 435–443.
Chitsaz, H., Amjady, N., Zareipour, H., 2015. Wind power forecast using wavelet neural network trained by improved Clonal selection algorithm. Energy

Convers. Manag. 89, 588–598.
Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach. Learn. 20 (3), 273–297.
Dai, S., Niu, D., Han, Y., 2018. Forecasting of power grid investment in China based on support vector machine optimized by differential evolution algorithm and grey wolf optimization algorithm. Appl. Sci. 8 (4), 636.
Eissa, M., Yu, J., Wang, S., Peng, L., 2018. Assessment of wind power prediction using hybrid method and comparison with different models. J. Electr. Eng. Technol. 13 (3), 1089–1098.
Elaziz, M.A., Xiong, S., Jayasena, K.P.N., Li, L., 2019. Task scheduling in cloud computing based on hybrid moth search algorithm and differential evolution. Knowl. Based Syst. 169, 39–52.
Engie, 2018. The La Haute Borne wind farm. https://opendata-renewables.engie.com/explore/?sort=modified.
Fang, S., Chiang, H.-D., 2017. A high-accuracy wind power forecasting model. IEEE Trans. Power Syst. 32 (2), 1589–1590.
Gao, W., Darvishan, A., Toghani, M., Mohammadi, M., Abedinia, O., Ghadimi, N., 2019. Different states of multi-block based forecast engine for price and load prediction. Int. J. Electr. Power Energy Syst. 104, 423–435.
Ghadimi, N., Akbarimajd, A., Shayeghi, H., Abedinia, O., 2018. Two stage forecast engine with feature selection technique and improved meta-heuristic algorithm for electricity load forecasting. Energy 161, 130–142.
Haque, A.U., Nehrir, M.H., Mandal, P., 2014. A hybrid intelligent model for deterministic and quantile regression approach for probabilistic wind power forecasting. IEEE Trans. Power Syst. 29 (4), 1663–1672.
Hariharan, M., Sindhu, R., Vijean, V., Yazid, H., Nadarajaw, T., Yaacob, S., Polat, K., 2018. Improved binary dragonfly optimization algorithm and wavelet packet based non-linear features for infant cry classification. Comput. Methods Progr. Biomed. 155, 39–51.
Iversen, E.B., Morales, J.M., Moller, J.K., Trombe, P.-J., Madsen, H., 2017. Leveraging stochastic differential equations for probabilistic forecasting of wind power using a dynamic power curve. Wind Energy 20 (1), 33–44.
Jiang, Y., Chen, X., Yu, K., Liao, Y., 2017. Short-term wind power forecasting using hybrid method based on enhanced boosting algorithm. J. Mod. Power Syst. Clean. Energy. 5 (1), 126–133.
Jiao, R., Huang, X., Ma, X., Han, L., Tian, W., 2018. A model combining stacked auto encoder and back propagation algorithm for short-term wind power forecasting. IEEE Access 6, 17851–17858.
Karakus, O., Kuruoglu, E.E., Altinkaya, M.A., 2017. One-day ahead wind speed/power prediction based on polynomial autoregressive model. IET Renew. Power Gener. 11 (11), 1430–1439.
Kim, D., Hur, J., 2018. Short-term probabilistic forecasting of wind energy resources using the enhanced ensemble method. Energy 157, 211–226.
Liu, R.S., Peng, M.F., Xiao, X.H., 2018a. Ultra-short-term wind power prediction based on multivariate phase space reconstruction and multivariate linear regression. Energies 11 (10), 17.
Liu, T., Liu, S., Heng, J., Gao, Y., 2018b. A new hybrid approach for wind speed forecasting applying support vector machine with ensemble empirical mode decomposition and cuckoo search algorithm. Appl. Sci. 8 (10), 1754.
Liu, T., Wei, H., Zhang, K., 2018c. Wind power prediction with missing data using Gaussian process regression and multiple imputation. Appl. Soft Comput. 71, 905–916.
Mirjalili, S., 2015. The ant lion optimizer. Adv. Eng. Software 83, 80–98.
Mirjalili, S., 2016. Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. Neural Comput. Appl. 27 (4), 1053–1073.
Mirjalili, S., Lewis, A., 2016. The whale optimization algorithm. Adv. Eng. Software 95, 51–67.
Mirzapour, F., Lakzaei, M., Varamini, G., Teimourian, M., Ghadimi, N., 2019. A new prediction model of battery and wind-solar output in hybrid power system. Int. J. Ambient. Intell. Humanized. Comput. 10 (1), 77–87.
Mladenovic, I., Markovic, D., Milovancevic, M., Nikolic, M., 2016. Extreme learning approach with wavelet transform function for forecasting wind turbine wake effect to improve wind farm efficiency. Adv. Eng. Software 96, 91–95.
Osorio, G.J., Matias, J.C.O., Catalao, J.P.S., 2015. Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information. Renew. Energy 75, 301–307.
Qureshi, A.S., Khan, A., Zameer, A., Usman, A., 2017. Wind power prediction using deep neural network based meta regression and transfer learning. Appl. Soft Comput. 58, 742–755.
Ranjini, S.K.S., Murugan, S., 2017. Memory based Hybrid Dragonfly Algorithm for numerical optimization problems. Expert Syst. Appl. 83, 63–78.
Ren, Y., Suganthan, P.N., Srikanth, N., 2015. Ensemble methods for wind and solar power forecasting-A state-of-the-art review. Renew. Sustain. Energy Rev. 50, 82–91.
Shao, H., Deng, X., Jiang, Y., 2018. A novel deep learning approach for short-term wind power forecasting based on infinite feature selection and recurrent neural network. J. Renew. Sustain. Energy 10 (4), 043303.
Shen, Y., Wang, X., Chen, J., 2018. Wind power forecasting using multi-objective evolutionary algorithms for wavelet neural network-optimized prediction intervals. Appl. Sci. 8 (2), 185.
Soualhi, A., Medjaher, K., Zerhouni, N., 2015. Bearing health monitoring based on hilbert-huang transform, support vector machine, and regression. IEEE Trans. Instrum. Meas.t 64 (1), 52–62.
Storn, R., Price, K., 1997. Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces. J. Glob. Optim. 11 (4), 341–359.
Sun, G., Jiang, C., Cheng, P., Liu, Y., Wang, X., Fu, Y., He, Y., 2018. Short-term wind power forecasts by a synthetical similar time series data mining method. Renew. Energy 115, 575–584.
Wan, C., Lin, J., Wang, J., Song, Y., Dong, Z.Y., 2017. Direct quantile regression for nonparametric probabilistic forecasting of wind power generation. IEEE Trans. Power Syst. 32 (4), 2767–2778.
Wang, J.Z., Hu, J.M., 2015. A robust combination approach for short-term wind speed forecasting and analysis - combination of the ARIMA (autoregressive integrated moving average), ELM (extreme learning machine), SVM (support vector machine) and LSSVM (least square SVM) forecasts using a GPR (Gaussian process regression) model. Energy 93, 41–56.
Wu, D., Qu, Z.S., Guo, F.J., Zhu, X.L., Wan, Q., 2019. Hybrid intelligent deep kernel incremental extreme learning machine based on differential evolution and multiple population grey wolf optimization methods. Automatika 60 (1), 48–57.
Xiang, W.L., Zhu, N., Ma, S.F., Meng, X.L., An, M.Q., 2015. A dynamic shuffled differential evolution algorithm for data clustering. Neurocomputing 158, 144–154.
Yang, T.-C., Yu, P.-S., Lin, K.-H., Kuo, C.-M., Tseng, H.-W., 2018. Predictor selection method for the construction of support vector machine (SVM)-based typhoon rainfall forecasting models using a non-dominated sorting genetic algorithm. Meteorol. Appl. 25 (4), 510–522.
Yuan, X., Chen, C., Yuan, Y., Huang, Y., Tan, Q., 2015. Short-term wind power prediction based on LSSVM-GSA model. Energy Convers. Manag. 101, 393–401.
Yuan, X., Tan, Q., Lei, X., Yuan, Y., Wu, X., 2017. Wind power prediction using hybrid autoregressive fractionally integrated moving average and least square support vector machine. Energy 129, 122–137.
Zhang, J., Cui, M., Hodge, B.-M., Florita, A., Freedman, J., 2017. Ramp forecasting performance from improved short-term wind power forecasting over multiple spatial and temporal scales. Energy 122, 528–541.
Zhao, H., Zhao, H., Guo, S., 2018. Short-term wind electric power forecasting using a novel multi-stage intelligent algorithm. Sustainability 10 (3), 881.
Zjavka, L., Misak, S., 2018. Direct wind power forecasting using a polynomial decomposition of the general differential equation. IEEE Trans. Sustain. Energy 9 (4), 1529–1539.
Zuo, X.Q., Xiao, L., 2014. A DE and PSO based hybrid algorithm for dynamic optimization problems. Soft Computing 18 (7), 1405–1424.